Evolving Creatures That Can Learn by Imitation: Apprentice Behavior and Its Role in Robot Motor Learning

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Abstract

The approach presented here argues in favor of a methodology of evolving robotic systems that are fitted for learning from similar creatures in their environment, i.e. exhibit an apprentice behavior. *Ideas expressed by Turing, Wiener and Varela in their works are recalled in support of this view. An individual system that is adapted for learning from other fitted individuals performing in the same environment is proposed and it is sugessted how such a system may be obtained through evolution. As a particular implementation of such a system, an anthropomorphic manipulator is considered, which is assumed to have gained this ability. Its motor development is outlined with the apprentice behavior supporting the transition from self-learning of sensory-coordination to teacher-based learning.*

Keywords

EVOLUTION AND LEARNING – ROBOT LEARNING – BEHAVIOR-BASED ROBOTS

1 Being adapted for learning

It is important to notice that most of the human knowledge and abilities (allowing in the end survival) are *learned from other humans*. This particular quality of **being adapted for learning** may be the most important quality determining the fitness of the human species.

As Wiener remaks in this sense, "Indeed, it may be said that a large part of the phylogenetic learning of man has been devoted to establishing the possibility of good ontogenetic learning" [WIENER61].

Recently, in Varela's work, a similar idea is sugessted, that adaptation is not reffering to the form of design or construction that matches optimally a physical situation, but rather adaptation referrs to the *process* involved, i.e. to *adapting* [VARELA93].

The "classic" approach in evolutionary-based systems is to derive systems that are adapted to an environment. In recent research, evolutionary processes were used for producing systems that can learn. Chalmers [CHALMERS90] has shown that learning rules in neural networks can be obtained by evolution. He used evolutionary algorithms to search the weight updating functions in a neural network and was able to derive the classic delta rule. Associative learning was evolved in simulations by Todd and Miller [TODD91].

The approach proposed in the present paper is to select structures that have the ability to learn from other structures in the same population (same generation). Thus the focus is not to learn from environment (even though this is preserved as a feature) but to learn from other individuals from the same generation, who found some good solutions, i.e. are fitted.

There is some support for such an approach in Turing's "cultural search" [TURING92] (see below). In fact, many of the ideas that received high attention recently can be found in Turing's work. In his writings on "Intelligent Machinery", he reffers to "intelectual, genetical and cultural searches". The intellectual search is briefly a search for combinations with particular properties and was generaly dealed with by classic Artificial Intelligence. The genetical or evolutionary search is that "by which a combination of genes is looked for, the criterion being survival value", a current idea for evolutionary computationists but, from what is implied in the context, more towards such a search as support for intellectual activity and in this sense closer to Siefkes' evolutionary thinking (see [SIEFKES92]). In relation with the "cultural search" Turing writes that "...the isolated man does not develop any intelectual power. It is necessary for him to be immersed in an environment of *other men*, whose techniques he absorbs...". The search is carried out by community as a whole, rather than by individuals. The "social-oriented" aspect of such a view is not far from fundamental ideas in current artificial life research. However, in this context, what this paper intends to address is rather the ability of individuals of absorbing techniques from others in the environment, and how to evolve individuals with such ability.

2 Developing an apprentice behavior

Consider a search problem, several individuals attempting to find a solution and a fittness evaluation procedure. Particular individuals can monitor others in their search method and get the information on others fitness. It is said that an individual is exhibiting an *apprentice behavior* if it is modifying its (search) behavior imitating the behavior of a more (most) fitted one, increasing thus its fitness. In such conditions, the fitness increment can be an indicator of the adaptive proprety of the individual and is the criterion for selection. An evolutionary algorithm taking in consideration this requirement, seeking the selection of a population fitted for learning from other members of the population, can be outlined as having the following major steps for the performance/evaluation part:

- behave (action)
- First fitness evaluation, fit_1
- look around at other individuals in the population and change own behaviour as to *imitate* the best fitted's behavior (self-reorganize using the information about the other's actions performed for achieving the goal)
- behave
- Second fitness evaluation, fit_2
- Evaluation of fitness increment (improvement = how much has been learned from peers), $fit_2 - fit_1$

Thus, selection ensures that individuals that can learn best from other ones which found a solution (maximum fit_i) are promoted for breeding. Combinations between fitness and fitness increment can be attempted as selecting criteria. Thus, the selection promotes individuals able to adapt themselves to the environment in one generation, by observing the adapted ones.

3 Motor learning in anthropomorphic manipulators

3.1 Aproaches for robot motor learning

Current work on modelling motor learning is streamed into two directions. Researchers following a first direction are primarily concerned with the early stages of learning, i.e. the development of *sensory-motor coordination* and follow in some respect Piaget's ideas on circular reaction and development of sensorimotor coordination at children (robots perform actions and perceive their effects, correlating actions with perceptions). Implementation results of this work are robots that learn by exploration, without having an initial model, and are able to achieve the coordination that enables them to grasp and track moving objects. These robots can be considered as entering a class of "animats".

A second direction is followed by researchers that are primarily targeting systems able of ***skill acquisition***. Researchers in this category develop systems that start learning based on a previously embedded-in-the-system knowledge, introducing into systems patterns of demonstrated movement or knowledge expressed by a human.

Investigation of learning in between this two stages may provide the base for an integrated approach on robot motor learning. The solution proposed here is to use evolutionary or conditioning methods to induce an apprentice behavior to the robot. Remark that for such robots, to follow a teacher's indication is not something that is programmed in before, but must come in the learning process, an apprentice behavior must be developed. These robots are imagined as behavior-based robots and different learning stages are considered as behaviors in a subsumption architecture.

3.2 Learning as a behavior in a subsumption architecture

Brooks [BROOKS91] argues for a new methodology of building robots. In contrast to the perception - modelling, planning, task execution, motor control mapping between sensors and actuators, he proposes a decomposition in terms of behavior-generating modules, each of which connects sensing to action. The behaviors developed by such robots start from simple (but complete) behaviors such as locomotion and become increasingly complex. In here it is proposed to consider learning as a behavior and consequently consider a behavior-based subsumption architecture as presented below.

- (iii) learning from a teacher
- (ii) developing an apprentice behavior
- (i) self-learning of sensorimotor coordination

A first level of learning consists in the development of the sensorimotor coordination, with a following level of learning being the development of an 'apprentice behavior' and the final level of learning being the supervised learning from a teacher.

3.3 Robot and teacher

Initially a population of simulated robots is used for evolving structures exhibiting aprentice behavior. (A reinforcement-based method could have been used, in which case the robot was rewarded when it exhibits an arm posture close to teacher's arm posture. The fitness can be given by the closeness to teacher's posture, only those who obey can survive! This determines the robot to *learn that it is useful to learn from a teacher*). A sucessful structure is then transplanted to the real robot.

The robot is now in an environment in which he is not alone, but a similar *creature* exists and exhibits a behavior (Figure 1). The robot attempts to imitate human arm movement.

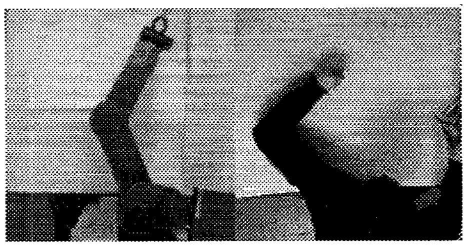

Figure 1. Robot and creature in robot's world (future teacher)

4 Conclusion

The paper presents some arguments for the utility of evolving systems that exhibit an apprentice behavior, i.e. systems that are able to learn from more fitted ones during the same generation. Thus, a high fitness improvement (possible correlated with absolute fittness) is determinant is the selection process. An application of such a system is sugested as being useful for providing the link between self-learning of sensorimotor coordination and teacher-based learning, for the case of anthropomorphic manipulators. Some aspects referring to such a system under development are briefly presented.

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